# Ocean Satellite Observations and Challenges

Robert N. Miller

College of Oceanic and Atmospheric Sciences
Oregon State University
Corvallis, OR 97330

#### **Outline**

- Introduction
- Satellite observations:
  - What are they,really?
  - What information do they really contain?
- Interdisciplinary oceanography
- Representation Error
- Challenges

### A Modeler's View of Satellite Data

The good news:

- Extensive spatial coverage
- A variety of data types:
  - SST
  - SSH
  - Wind
  - Color
  - Salinity (coming soon!)
- Instruments keep getting better!

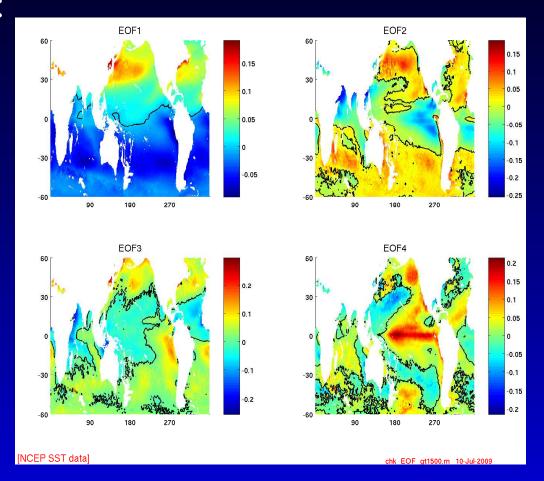
### A Modeler's View of Satellite Data

The not-so-good news:

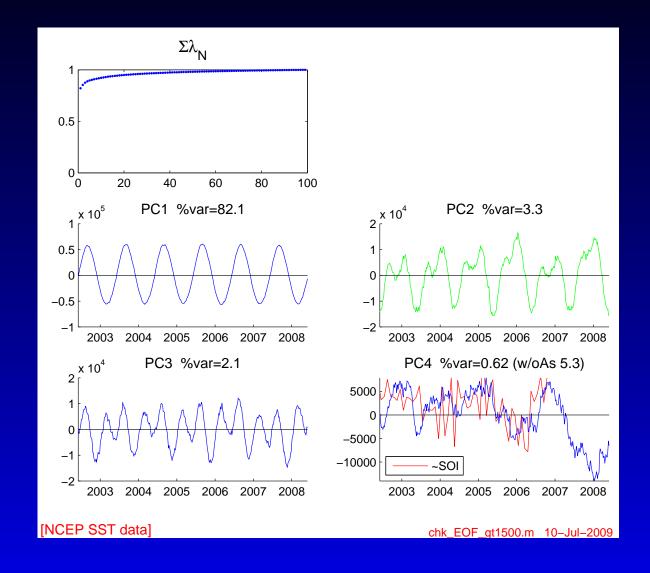
- Surface only
- Short and often gappy time series
- Changes in instruments make statistics difficult
- Some measured quantities are hard to relate to model state variables
- One exception is altimetry, but altimeter data are not synoptic

# What Will Satellite Data Tell Us?

begin with SST:

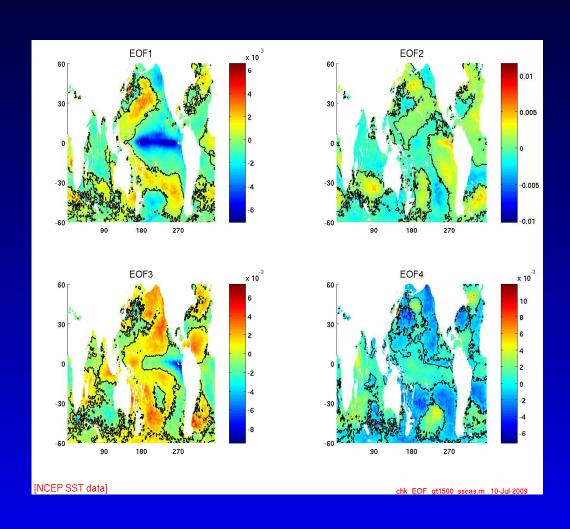


## **EOF** Amplitudes

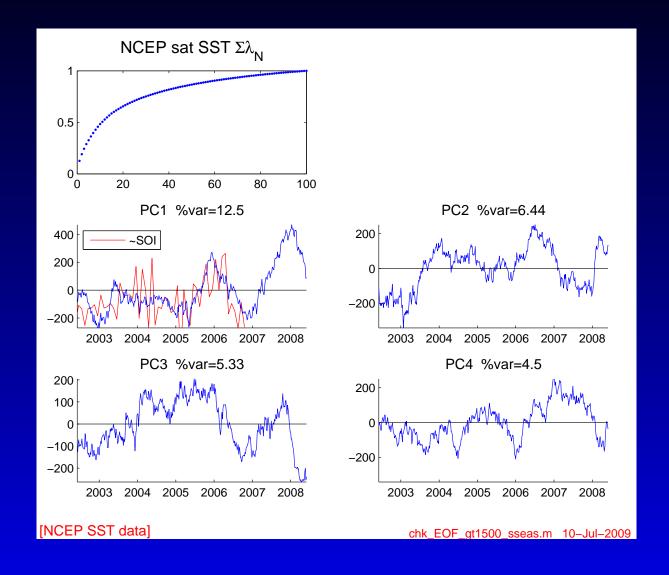


# What Will Satellite Data Tell Us?

Now take out the seasonal cycle:



## **EOF** Amplitudes

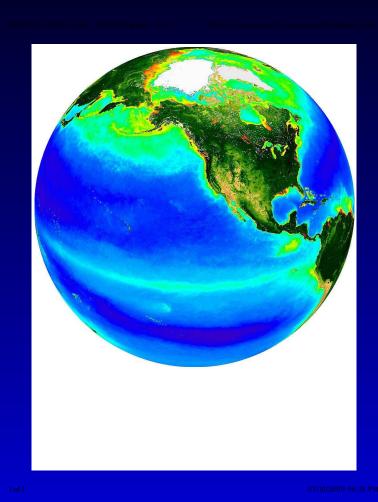


## Satellite Observations: what are They?

#### Usual DA setup:

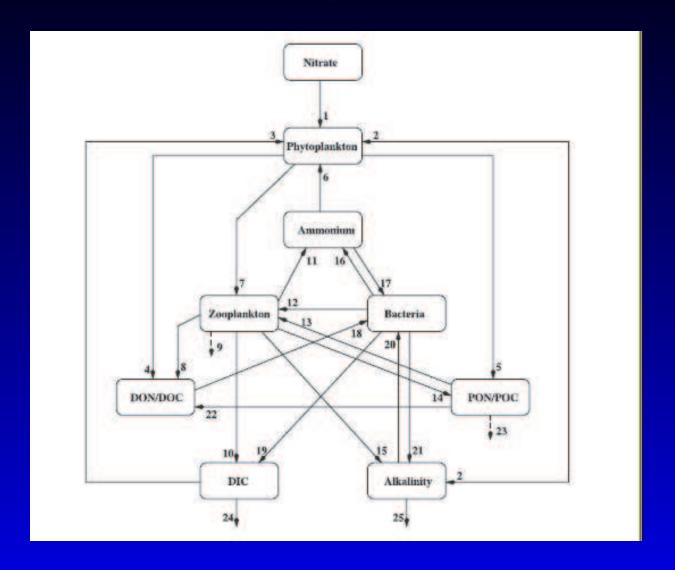
- Model state vector x
- Modeled value of observed quantity is Hx
- What do we use for *H*?

## Ocean Color



... how can we use it?

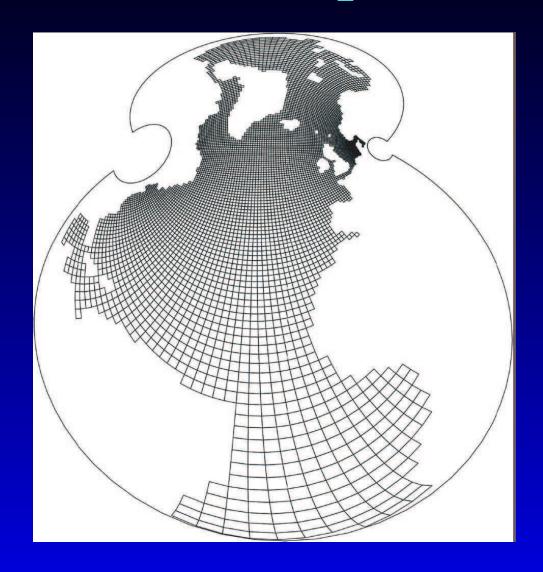
## Ocean Ecology Models



## The Physical Model

- A version of the Micom isopycnic model of the north Atlantic
- 17 layers
- Uppermost layer divided into two biochemical layers
- Curvilinear grid
- Biological model does not affect physical model

## Grid for Coupled Model



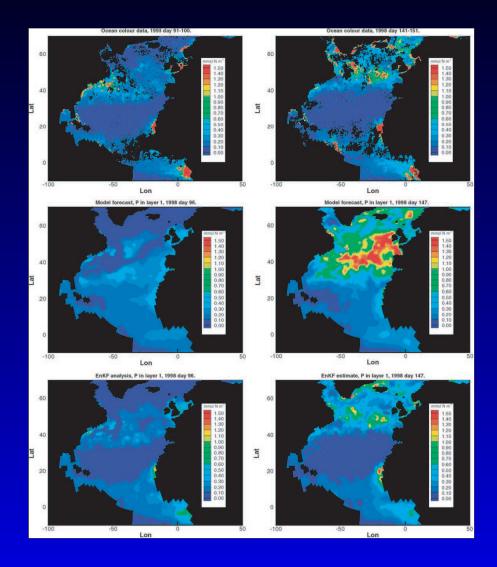
#### The Ensemble Kalman Filter

- Initial conditions and forcing perturbed in physical model
- No perturbations added to biological state variables in order to avoid the possibility of negative concentrations
- Chlorophyll data converted to phytoplankton biomass by:

$$C = \rho_{max}(Chl_a/(Chl_a + K_{1/2}))Chl_a$$
. C relates to P by a fixed ratio.

• 100 ensemble members in the main experiment; similar results obtained with much smaller ensembles

# EnKF Results from Coupled Model



#### **Particle Filters**

- Estimate the (possibly non-Gaussian) distribution with an ensemble
- Update the ensemble when data become available
- One way to do this is to re-sample, with replacement:
  - 1. For each member, calculate the probability that the member could have given rise to the actual observation
  - 2. Normalize the probabilities so that their sum is 1.
  - 3. Assign each member a sub-interval of the unit interval
  - 4. Generate a uniformly distributed random number between 0 and 1. Ocean Satellite Observations and Challenges p.16/3:

#### The SIR Filter

- Resampling, continued:
  - 1. Find the member's sub-interval into which the random number falls, and choose that ensemble member for the next interval
  - 2. Continue this process to fill the ensemble
- This is Sequential Importance Resampling

#### **Particle Filters**

- The SIR filter has been applied with some success in ocean modeling
- Like most particle filters it requires very large ensembles to avoid sample impoverishment

## Representation Error

The big question: What is truth?

## Data Assimilation: Assumptions

#### Given

- A model:  $\mathbf{u}_t L\mathbf{u} = \mathbf{f}$
- Chosen to mimic the "true" state  $\mathbf{u}^{(t)}$  which evolve according to:

$$\mathbf{u}_t^{(t)} - L\mathbf{u}^{(t)} = \mathbf{f} + \mathbf{b}; \ \mathbf{b} \ random$$

- Observations  $\mathbf{z} = H\mathbf{u}^{(t)} + \mathbf{e}_{obs}$ ; H defines the relation between the state vector and the observed quantities
- Question for Today: What, *precisely*, is  $\mathbf{u}^{(t)}$ ?

#### In Search of the True State

- The ocean measured by instruments doesn't know about physical approximations, coarse resolution or their consequences
- It is not subject to the limitations in computing power that restrict models to coarse resolution
- Measurements are not subject to the same requirements for approximate physical parameterizations

So ask: What quantity in nature is the "true" value of the model state?

No specific answers today; Rather a suggestion for what to do while we are waiting.

## **Representation Error**

- Data assimilation makes use of data misfits, aka innovations:  $\mathbf{z} H\mathbf{u}^{(f)}$
- $\mathbf{u}^{(f)}$  is the forecast state
- Let  $\tilde{\mathbf{u}}^t$  be the "true" ocean, as the instruments measure it.

### **Representation Error**

Write the innovation:

$$\mathbf{z} - H\mathbf{u}^{(f)} = \mathbf{z} - \mathbf{z}^{(t)} + \mathbf{z}^{(t)} - H\mathbf{u}^{(f)}$$
$$= \epsilon^0 + \mathbf{H}(\tilde{\mathbf{u}}^{(t)} - \mathbf{u}^{(t)}) + \mathbf{H}(\mathbf{u}^{(t)} - \mathbf{u}^{(f)})$$

- $\epsilon^0 = \mathbf{z} \mathbf{z}^{(t)}$ , the instrument error
- $\mathbf{H}(\tilde{\mathbf{u}}^{(t)} \mathbf{u}^{(t)})$  is representation error
- Estimates of its statistics must appear in the terms reserved for instrument error
- $\mathbf{u}^{(t)} \mathbf{u}^{(f)}$  is the forecast error

### Estimating Representation Error

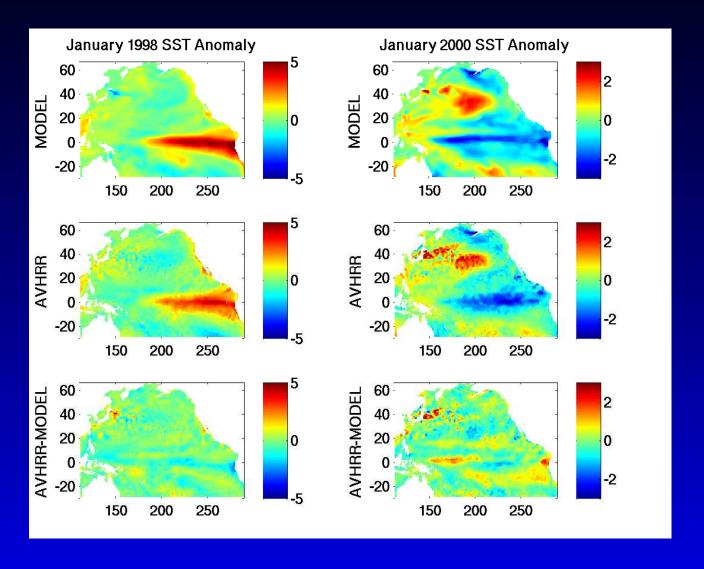
Our method for estimating the representation error for SST:

- 1. Generate a long model run
- 2. Calculate EOFs of the model run, considered as a matrix whose (i, j) element is the value of state element j at time i
- 3. Determine the number of meaningful degrees of freedom
- 4. Project the innovations on the meaningful singular vectors
- 5. Subtract the result from the innovations.
- 6. The difference is an estimate of the representation error

#### **Pacific Circulation Model**

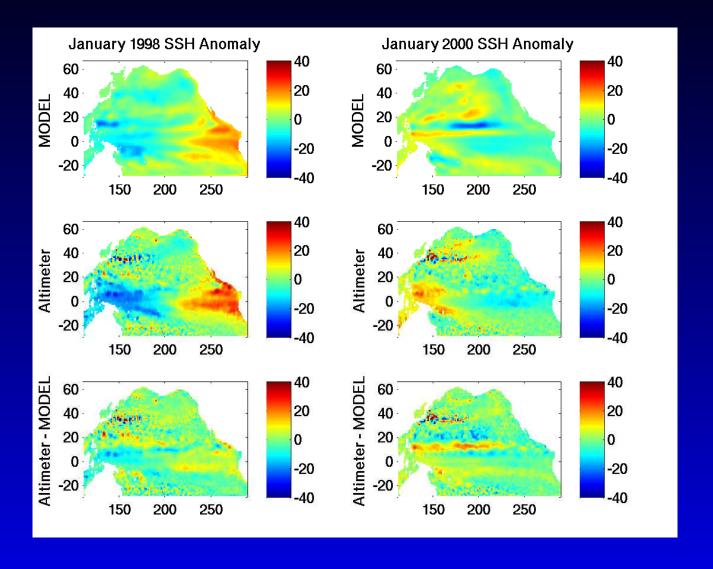
- Parallel Ocean Program (POP)
- Domain:
  - $105^{o}E$  to  $85^{o}W$
  - $30^{o}S$  to  $64^{o}N$
- Resolution
  - 1° at the Equator, Mercator projection
  - 0.5° average resolution
  - 50 vertical levels, 25 in top 500m
- 25 years (1978-2002), forced by NCEP/NCAR reanalysis
- Initialized from Levitus, 30 year spinup

#### **Model and AVHRR Anomalies**



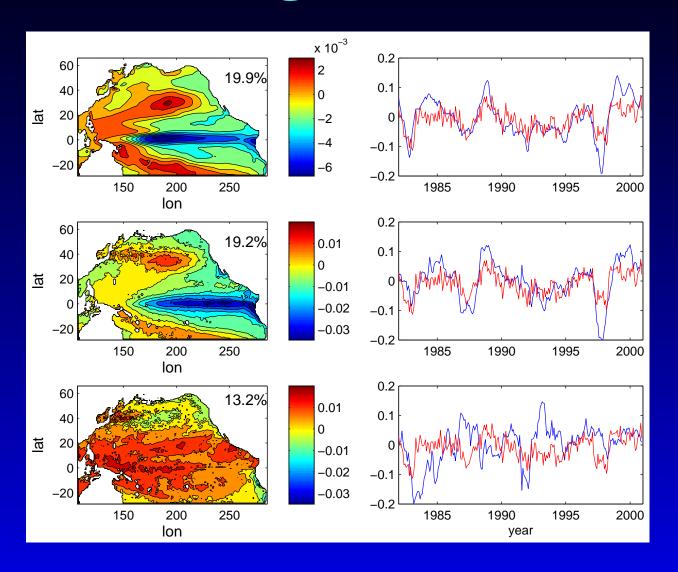
Model SST anomalies (top), AVHRR SST (middle) and data-model misfit (bottom) for 2 different years parents and data-model misfit (bottom) are 2 different years parents and data-model misfit (bottom).

#### **Model and SSH Anomalies**



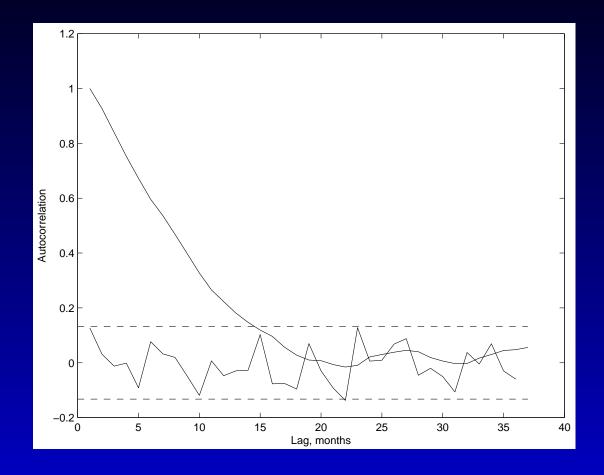
Model SSH anomaly (top) AVISO SSH (middle) and data-model misfit (bottom) for 2 different years Challenges - p.27/3.

## Leading EOFs



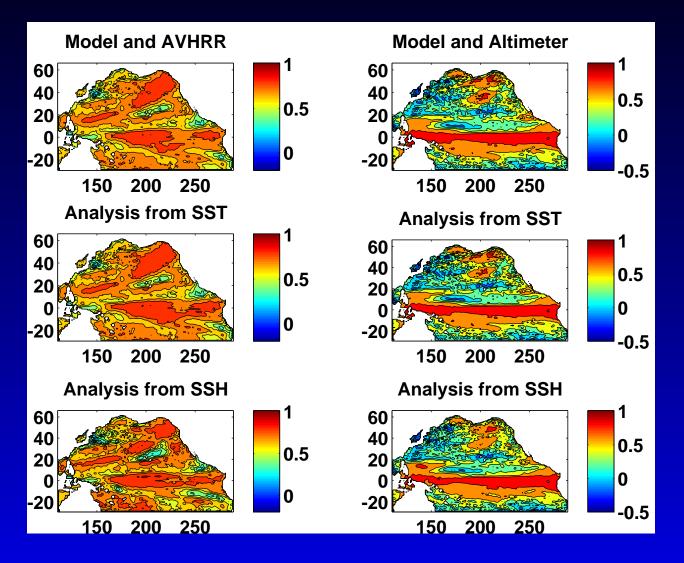
Leading EOFs and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; AVHRR SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; Misfit, Red = SOI, and PCs for (top to bottom) Multivariate model SST; Misfit, Red = SOI, and Avent Misfit model SST; Misfit model

#### **Misfit EOF Time Series**



Autocorrelations of time series of SST misfit PCs. Upper curve: lead PC; Lower curve: residuals from a fitted AR(1) process

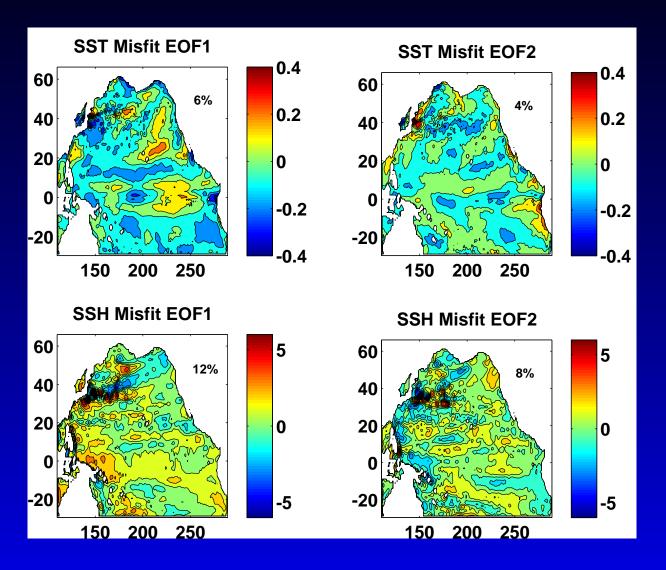
#### **Data Assimilation Results**



Correlation with observed SST (left) and SSH (right)

Top to bottom: No assim; assim of SST: SSH (challenges - p.30/3)

### Representation Error EOFs



EOFs of the SST and SSH representation error. Percentages of total orthogonal space variance are shown.

## Summary of 1° Pacific Model Results

- Lead EOFs of model and observed SST dominated by SOI
- Lead EOF of model-data misfit is well-modeled by an AR(1) process
- Estimates of representation error are as we expect
- Our estimates lead to ensembles with statistical properties of SST misfits

## Summary

- New remotely sensed data sets will present new challenges
- Much satellite data comes in forms that are not easily represented in terms of dynamical variables
- Least-squares methods may be insufficient; we may have to work with explicitly nonlinear and/or Bayesian methods such as particle filters
- We will need to deal explicitly with representation error
- Satellite data sets provide new and great opportunities in interdisciplinary oceanography